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Trade-off analysis for infrastructure management: new approaches to cross-asset challenges

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Abstract

As transportation infrastructure managers pursue performance-based management, increased scrutiny is rightfully imposed by the stakeholders (tax-payers and their legislative representatives).
The performance of public transportation agencies is not evaluated on a single asset type (i.e. on Pavement, or Bridges alone) but on the system as a whole (cross-assets). Many commercial software packages are focused on managing a single asset type making cross-asset analysis difficult. However, a main problem for transportation agency managers is how to split available budget among different types of assets to provide the best overall performance to the public stakeholders.
This paper focuses on two different approaches to the Cross-Asset Problem (CAP) and demonstrates, using real data examples, how optimal budget distribution for various asset types can be found for large agencies.
The paper formulates individual asset management as an integer optimization problem (IP).
It then discusses two approaches to the CAP. The first approach assumes that overall agency performance can be expressed as a linear combination of individual asset type performances. In this case the CAP can be formulated as an Integer Optimization Problem (IP) where its objective and constraints are defined as a simple linear combination of the objectives/constraints for corresponding asset types. Model formulation, running times and optimal budget distributions using real transportation agency data are presented for this approach.
The second approach requires no assumptions on the CAPs objective formula and considers separate asset type problems as a black box which, for a given budget distribution, returns the best overall performance for that asset type. A Derivative Free Optimization algorithm is presented for this setup, showing running time and final budget distributions for several examples.

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Finally, the paper outlines the advantages and disadvantages of each approach and provides guidance on when each approach should be used.

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Keywords: Asset management; trade-off; analysis; infrastructure management; cross-asset; integer optimization

1. Introduction

Public transportation agency performance is not evaluated on a single asset type like Pavements or Bridges alone, but on the network as a whole (cross-assets), hence, multi-asset management tools are needed to manage the infrastructure.

Many commercial software packages are focused on managing a single asset type and provide a way to do a what-if analysis for that one asset type. There is no easy way to combine several such packages into an efficient cross-asset planning tool, which makes trade-off analysis difficult. An investigation performed by Caltrans Division of Research and Innovation (DRI) showed that currently only two agencies perform cross-asset management - North Carolina DOT and Utah DOT. AgileAssets is among the first to provide a comprehensive and powerful cross-asset Maintenance and Repair (M&R) planning tool to transportation agency managers that allows them to manage the strategic portfolio while providing detailed plans for specific goals. This is the solution used by North Carolina DOT.

This paper presents two approaches for the Cross-Asset Problem (CAP) and demonstrates, using real data examples, how desirable system performance can be achieved by grouping and scheduling projects across two asset types (pavements and bridges for this example). One of the key decisions made on the transportation network by executives is how to split available funds between different asset types to maximize overall infrastructure performance. For example, North Carolina DOT is responsible for maintaining both bridges and pavements. What amount should they spend on bridges and what amount on pavements? More importantly, what would be the impact of different budget distributions on overall performance? This is a typical trade-off analysis problem that can be solved using CAP.

We formulate management of individual assets as an integer optimization problem (IP). The paper discusses two approaches to the CAP. The first approach assumes that transportation network performance can be expressed as a linear combination of individual asset performances. In this case the CAP can be formulated as an Integer Optimization Problem (IP) with objective and constraints defined as a simple linear combination of the objective and constraints for the specific asset types. Model formulation, running times and optimal budget distributions using real transportation agency data for this approach are presented below.

The second approach does not have any assumptions on the CAP's objective formulation and considers separate asset type problems as a black box, which for a given budget distribution returns the best overall performance for that asset type. A Derivative Free Optimization algorithm for this setup and its running time and final budget distributions for different instances are presented.

2. Cross asset problem Structure

The Cross Asset Model can be used to combine single asset optimization models for different asset types. In order to solve the CAP efficiently the single asset optimization models used should be computationally attractive. The authors found that a strategy based Integer Programming formulation is a good candidate for use as a single asset model. There are several reasons in favor of that choice. First, special heuristics and solver adjustments can be used to reduce running times, making it possible to solve large networks. Second, this formulation allows for flexible asset performance models and variable model size. For details see Scheinberg and Anastasopoulos [2010], Bhargava et al. [2013].

The following is a brief description of generalized asset management model formulation that utilizes strategies:

Sets:
I - set of assets (for example, road sections)
J_i - set of available strategies for asset i
T - optimization time horizon
A - set of attributes that describe a strategy
$A_{i,j,t}$ - value of attribute A for asset i under strategy j for years $t = 1, ..., T$
K - a set of rules for building constraints. It includes R^k - area of application and C^k - limit value of constraint k
Optimization model has only binary decision variables x_{ij}:

$$x_{i,j} = \begin{cases} 1, & \text{if strategy } j \text{ is selected for asset } i \\ 0, & \text{otherwise} \end{cases}$$

The Objective function and each essential constraint are associated with some attribute so that coefficients are obtained from attribute profiles. For example, if the objective is to maximize the weighted (by attribute $Weight_i$) average of attribute PCI then $PCI_{i,j,t}Weight_i$ will give us objective coefficients $Obj_{i,j}^t$ for strategy j of asset i in year t.
The Single Asset Management Model with K constraints has the form:

$$\begin{aligned} &\min_x(\max_x) && \sum_{i\in I}\sum_{j\in J_i}\sum_{t\in T} Obj_{i,j}^t x_{i,j} \\ &\text{Subject to} && \sum_{i,j,t\in R^k} Constr_{i,j,t}^k x_{i,j} \le (\ge) C^k, k \in K \\ &&& \sum_{j\in J_i} x_{i,j} = 1, i \in I \\ &&& x_{i,j} \text{ - binary}, i \in I, j \in J_i, \end{aligned} \tag{1}$$

Assuming this IP approach can be used as single asset model, there are two possible out- comes of combining several such models into one CAP model. First, the CAP Model can still be formulated as an IP, we will refer to it as BIG IP CAP model. Second, the CAP model can no longer be an IP. Which scenario occurs depends on the objective function that evaluates overall cross asset performance. If a linear combination of these single asset model objectives is used then it is possible to have a single BIG IP as CAP. It is also possible to get away with using minimum function of the single objectives (that are being maximized) via standard modelling technique. However, if the combined objective has a more complicated nonlinear form it is impossible to form a single IP problem, so special techniques must be used.

In the case of a linear combination of single objectives, creating the BIG IP problem is straightforward. The BIG IP has the same formulation as the Single Asset model mentioned above with appropriate expansion of sets I, J, A and K to incorporate several asset types and their strategies.

In the case when CAP becomes nonlinear, we propose to use a Derivative Free Optimization (DFO) approach that would explore T(M-1) dimensional space, so that annual budget distributions between M asset types can be varied. For two asset types the DFO optimization model has the form:

$$\max_{B_p, B_b} \quad H[F(B_p), G(B_b)] \tag{2}$$
$$B_p^t + B_b^t = B^t, t = 1, ..., T,$$

where B_p^t and B_b^t are pavements budget and bridges budget for year t. B^t is the total available budget for year t. $F(B_p)$ is an optimal performance of pavement network given vector of annual budgets B_p. $G(B_b)$ is an optimal bridge performance given vector of annual budgets B_b and function $H(x, y)$ measures combined performance of bridges and pavements.

This approach is attractive because there are no restrictions on the form of the objective function and the optimization model can be solved using existing DFO methods. However, DFO performance degrades as the number of constraints and variables increases. For the reason of simplicity additional assumption was made that budget distribution between asset types is constant across all years. This assumption effectively reduces the dimension of the DFO optimization model to just one variable. For this case the DFO optimization problem for two asset types is given by

$$\max_{B_p, B_b} \quad H[F(B_p), G(B_b)]$$
$$B_p + B_b = B \tag{3}$$

where B - total annual agency budget and B_p and B_b become scalars. In the future research the authors plan to investigate DFO performance without the budget assumption.

Note that the DFO approach might also be attractive if the user does not have full control over single asset optimization routines, i.e when only a black box optimization procedure for a specific asset type is given. In order for the DFO approach to work, what is needed is an ability to run single asset optimization with variable budgets. Of course this flexibility of the DFO approach comes at a price, mainly in terms of longer running times, and it remains to be seen if this approach is practical for solving very large problems.

3. Numerical results

This section applies the concepts by performing trade-off analysis on real data from a client. The client has one of the biggest road networks and largest bridge inventory in the United States. The goals are to demonstrate that these approaches can be successfully used on large real agency problems and that the comprehensive useful information required for transportation agency' managers can be obtained.

Results for two scenarios are demonstrated - a Division Scenario and an Agency Scenario. The Division Scenario is a smaller scenario and, as the name suggests, consists of data for just one division within the agency. The Agency Scenario will cover the entire agency network. The Division Scenario has 5,987 road sections that cover 10,239 lane miles of roads and 569 bridges. The Agency Scenario has approximately 102,000 sections that cover 162 thousand lane miles of roads and 14,050 bridges. Each scenario has 11 strategies designed for each road section and 26 strategies for each bridge. Using this data as input, single asset optimization model instances for pavement and bridges are formed for each scenario that optimizes average performance rating over 10 year time horizon subject to annual budgets. Note that this approach is not limited in any way to just this setup, many more constraints could be introduced for each year. This formulation was adopted to be simple and easy to follow.

Using single asset models and having just two asset types, it is possible to solve the CAP model using a simple graphical approach by evaluating $F(B_p)$ and $G(B_b)$ for various values of B_p and B_b and then calculating $H[F(B_p), G(B_b)]$. The results of such an exercise can be seen in Figure 1 for the Division Scenario and Figure 2 for the Agency Scenario. For this example, $H[x, y]$ is a simple linear combination of $F(B_p)$ and $G(B_b)$. Weights of (0.5, 0.5), (0.4, 0.6),(0.6, 0.4),(0.8,0.2) and (0.2, 0.8) were used. The total annual agency budget for the division was $50,000,000 and for the agency - $600,000,000. The current performance levels for bridges and pavements are represented by the dotted lines on the graph.

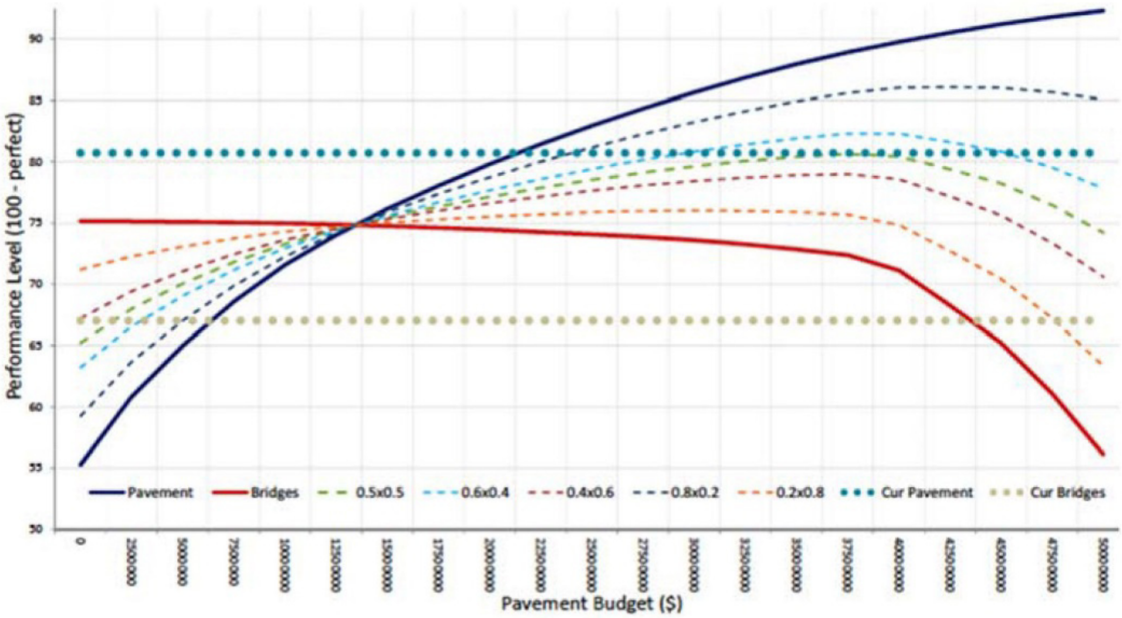

Fig. 1. Division Scenario Results.

Figure 1 and Figure 2 are very informative for the decision maker as the optimal budget distribution can be found. For example, using simple linear combination with weights (0.5, 0.5), the budget distribution of $37,500,000 for pavement and $12,500,000 for bridges is the optimal mix for the Division Scenario. In case of the Agency Scenario, using the same objective function, the optimal mix is $450 million for pavement and $150 million for bridges. You can also see what performance levels pavement and bridges respectively will achieve with this budget distribution.

There is low sensitivity of results obtained to the objective weights. When changing weights of the linear combination - the optimal distribution does not change significantly. Usually using a subjective combination of weights is a cause for concern. However knowing that slight changes in the weights does not lead to big changes in the optimal budget distribution can re- leave these concerns. This low sensitivity can be explained by the structural nature of bridges- it is very expensive to keep a bridge in excellent condition, however, keeping it in average condition costs significantly less.

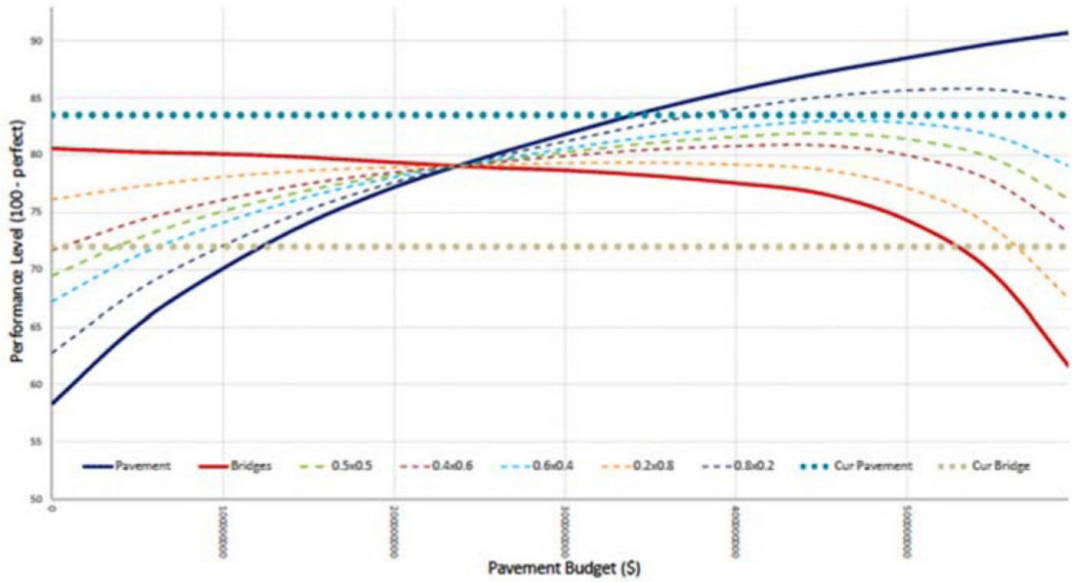

Fig. 2. Agency Scenario Results.

How long did it take to generate this plot? Thirteen evaluations for both $F(B_p)$ and $G(B_b)$ were performed. Calculations of $H[F(B_p), G(B_b)]$, once $F(B_p)$ and $G(B_b)$ are given are not time consuming. In the case of the Division Scenario thirteen evaluations of $F(B_p)$ and $G(B_b)$ took about 15 minutes. Twenty-six total single asset IPs solved to optimality, each run took no more than 35 seconds. Fifteen minutes for such an informative plot is acceptable. In the case of the Agency Scenario, 26 IPs took 40 minutes, about 93 seconds per instance. Now, 40 minutes might be too long, especially in cases where you want to know just the optimal budget distribution for a particular weight combination. This is where the BIG IP and DFO approaches come into play.

BIG IP CAP instances for the same set of weights as above were solved to optimality. Aver- age Annual budgets for Bridges and Pavement and running times for the Agency Scenario are presented in Table 1. As you can see, the optimal budget distribution can be found in no more than two minutes in comparison to 40 minutes of the head on approach.

Table 1. BIG IP CAP Results.

Obj. Weights		Avg Annual Budget		Run Time (seconds)
Pavement	Bridges	Pavement	Bridges	
0.5	0.5	$ 443,365,552	$ 156,333,365	77
0.6	0.4	$ 470,041,665	$ 129,806,675	121
0.4	0.6	$ 437,268,064	$ 162,239,131	65
0.2	0.8	$ 406,815,648	$ 193,147,737	83
0.8	0.2	$ 512,156,786	$ 87,225,466	52

The DFO approach was applied to the same five problems that the BIG IP CAP solved, i.e. using linear combination as the objective function. COBYLA algorithm of NLOPT optimization library for python was used. The objective evaluation function consisted of running separate IP solvers for bridges and pavements for provided budgets. The budgets in MPS files were modified before each solver execution. The optimality gap for the COBYLA algorithm was set to 0.02. Running times and number of iterations required for the algorithm to converge are presented in Table 2:

Table 2. DFO Approach CAP Results.

Obj. Weights		Avg Annual Budget		Run Time	Iterations
Pavement	Bridges	Pavement	Bridges	(seconds)	
0.5	0.5	$ 459,099,025.77	$ 140,900,974.23	958	14
0.6	0.4	$ 471,937,508.88	$ 128,062,491.12	1465	22
0.4	0.6	$ 433,289,109.68	$ 166,710,890.32	1173	16
0.2	0.8	$ 339,774,756.44	$ 260,225,243.56	1242	21
0.8	0.2	$ 509,935,400.59	$ 90,064,599.41	633	12

As seen from Table 2 the longest running time was about 25 minutes during which the algorithm had to perform 22 objective function evaluations. This resulted in solving 44 single asset type IPs which is 18 runs more than the head on approach, however, it took almost 15 minutes less. The DFO convergence path was through easy to solve single asset instances, which resulted in the savings of 15 minutes. On average running time for the DFO approach was about19 minutes and the average number of iterations was 17 with 34 single asset problems solved.

Note that the BIG IP model did not require that the budget for pavement and bridges must be the same across all years, hence, the difference in average annual budgets. There is also a small difference in the optimal values of the objective function. The DFO approach has consistently lower values but the difference between the two objectives never exceeds 0.55. This is the price of having equal budgets for pavement and bridges across all 10 years. See Table 3 for details:

Table 3. DFO Approach vs BIG IP: Objective values at Optimality.

Obj Weights		BIG IP			Derivative Free Optimization		
Pavement	Bridges	Pavement	Bridges	Comb	Pavement	Bridges	Comb
0.5	0.5	86.78	77.71	82.25	88.21	75.27	81.74
0.6	0.4	87.81	76.41	83.25	87.67	76.16	83.07
0.4	0.6	86.40	78.03	81.38	86.32	77.22	80.86
0.2	0.8	85.55	78.35	79.79	84.01	78.13	79.30
0.8	0.2	89.34	72.32	85.94	89.17	70.31	85.40

4. Conclusion

Transportation agency performance must be analyzed on a multi-asset level to see the “bigger picture”. Therefore it is important to have a tool that can perform an agency’s planning, taking its entire asset inventory into account. There are many examples of software that deal with just one asset type. This paper presented two techniques that allow optimizing several asset types at once.

The BIG IP CAP model is suitable to handle cases when it is possible to use a linear combination of separate asset types’ performances as the objective function. It is possible to solve a combined problem that has over 100,000 road sections and about 14,000 bridges in under 5 minutes. Unfortunately, it is not always possible to use a linear combination as an objective. The BIG IP CAP technique also relies on an assumption that users have direct control over the entire optimization process (such as procedures that form MPS file). When one of these two assumptions is false, another approach must be used.

The DFO approach is slower than BIG IP CAP when dealing with the same instances. How- ever, when dealing with a black-box situation (separate assets are analyzed by different pro- grams but the user has an API to perform the optimization routines) or when a nonlinear objective function must be used, then the Derivative Free Optimization approach could be a suitable and easy to implement option. Keep in mind, as reported by many researchers, the performance of Derivative Free Optimization algorithms degrades quickly as the number of decision variables grows but it is viable as long as there are no more than 20 decision variables and only a moderate number of constraints, so the practicality of this approach can be limited.

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